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(Article begins on next page)

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A BI-DIMENSIONAL INDEX FOR THE SELECTIVE ASSESSMENT OF MYOELECTRIC MANIFESTATIONS OF PERIPHERAL AND CENTRAL MUSCLE FATIGUE

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ABSTRACT

Two physiological factors are assumed in this paper to mainly determine the myoelectric manifestations of fatigue: 1) the decrease of the conduction velocity (CV) of motor unit action potentials (MUAP) (peripheral fatigue), and 2) the increase of MU synchronization by the central nervous system (central fatigue). To describe separately the peripheral and central components of the myoelectric manifestations of fatigue, we investigated the following indexes: 1) mean spectral frequency – MNF, 2) median spectral frequency – MDF, 3) root mean square – RMS, 4) average rectified value – ARV, 5) estimation of muscle fiber conduction velocity – ECV, 6) percentage of determinism – %DET , 7) spectral indexes defined as the ratio between signal spectral moments – FI_k, 8) MNF estimated by autoregressive analysis – MNF_{AR}, 9) MNF estimated by Choi-Williams time-frequency representation – MNF_{CWD}, 10) MNF estimated by continuous wavelet transform – MNF_{CWT}, 11) signal entropy – S, 12) fractal dimension – FD. The indexes were tested with a set of synthetic EMG signals, with different CV distribution and level of MU synchronization. The indexes were calculated on epochs of 0.5 s. It was observed that ECV is uncorrelated with the level of simulated synchronization (promising index of peripheral fatigue). On the other hand FD was the index least affected by CV changes and most related to the level of synchronism (promising index of central fatigue). A representative application to some experimental signals from vastus lateralis muscle during an isometric endurance test supported the results of the simulations. The vector *(ECV, FD)* is suggested to provide selective indications of peripheral and central fatigue. The description of EMG fatigue by a bi-dimensional vector opens new perspectives in the assessment of muscle properties, with potential application in both clinical and sport sciences.

1. INTRODUCTION

Despite the fact that fatigue is an experience of our daily life, its definition is very complex, not unique and controversial. In common language, fatigue may be described as a feeling or sensation of weakness or muscle pain or a decrement of performance, not easily suitable for quantification or measurement. Since the original work of Piper (1912), it was shown that during an isometric constant effort, albeit in absence of mechanical manifestations of fatigue, a number of modifications in surface EMG signal occur, generating the so-called myoelectric manifestations of fatigue. In such a way, fatigue can be assessed since the very beginning of a muscle effort.

Myoelectric manifestations of fatigue are induced by two main physiological factors: 1) the slowing of motor unit action potential (MUAP) during their travelling along muscle fibers, that is a variation of their conduction velocity (CV), and 2) the synchronization of motor units (MUs) by the central nervous system to increase the mechanical output when the whole MU pool is recruited. These two factors have different origins and affect the EMG signal in different ways (Merletti and Parker, 2004).

CV decrease during sustained isometric contractions is associated to a decrease in blood pH (Bouissou et al., 1989; Brody et al., 1991; Lindstrom et al., 1970; Komi et al., 1979). Lactate was largely considered the primary cause of the oxygen debt following exercise, a major cause of muscle fatigue, and a key factor in acidosis-induced tissue damage. Accumulation of lactic acid, however, was recently recognized as a process aimed to retarding the acidosis (Gladden et al., 2004; Robergs et al., 2004) instead of causing it. On the contrary, the lack of oxygen (Hogan et al., 2004; Russ et al., 2003) was considered as the main factor generating acidosis, in association with the accumulation of H^+ as a consequence of the ATP consumption.

The reduction of muscle fiber CV reflects in the frequency-domain as a scaling of the power density function (PDF) of the EMG signal towards lower frequencies (Lindstrom and Magnusson, 1977). As long as EMG signal can be considered a wide sense stationary (WSS) process (isometric constant force contractions segmented into epochs of 0.5-1 s) it is possible to compute the power

density function and extract spectral variables such as the mean or median frequencies (MNF and MDF) of the PDF, as suggested in early works (Chaffin, 1973; Lindstrom et al., 1970; Lindstrom and Magnusson, 1977; De Luca, 1984).

In the last decades a number of authors investigated the rate of change of EMG parameters such as estimated conduction velocity (ECV), MNF, MDF, root mean square (RMS), and average rectified value (ARV) during isometric fatiguing contraction. These variables correlate with fiber type distribution of the muscle (Kupa et al., 1995; Sadoyama et al., 1988; Komi et al., 1979; Gerdle et al., 1991; Mannion et al., 1998); they are also predictive of endurance time (i.e. the time for which a subject is able to maintain the requested mechanical task (Merletti and Roy, 1996)); they change as a function of the muscle position with respect to the electrodes on the skin (Rainoldi et al 2000) and in relation to limb position (Farina et al., 1999); they are related to age (Merletti et al., 2002), and to pathological conditions such as: neck pain (Falla et al., 2003), anorexia nervosa (Melchiorri and Rainoldi, 2006), hypobaric hypoxia (Casale et al., 2004), back pain (Roy et al., 1997), and other conditions (Drost et al., 2006).

Recently, new methods such as recurrence quantification analysis (RQA), ratio between spectral moments, continuous wavelet transform (CWT), time frequency representations (TFR), autoregressive (AR) analysis, signal entropy (S) were proposed to estimate myoelectric manifestations of fatigue (Filligoi and Felici, 1999; Farina et al., 2002; Dimitrov et al., 2006; Karlsson et al., 2000). As indicated in (Farina et al. 2002), separating the contribution of synchronization from other myoelectric manifestations of fatigue could be important to get insight into the muscle changes during fatigue and to distinguish among groups of subjects and/or muscles. The objective of this work is to compare different approaches, highlight their differences and limitations, and assess their sensitivities to CV and MU synchronization variations with special attention to the possibility of discerning between the two phenomena.

2. METHODS

The indexes listed in Table 1 were tested on simulated signals to assess estimators of myoelectric manifestations of muscle fatigue. A brief description of each fatigue index is provided in the Appendix.

Table 1 about here

2.1 Simulated Signals

A set of signals was simulated in order to evaluate the sensitivity of different indexes to central and peripheral fatigue. The three plane layer model (skin, fat, muscle) proposed by Farina and Merletti (2001) was used to simulate surface EMG signals. Muscle tissue was considered anisotropic while the other layers were isotropic (conductivities: σ_{skin} = 1 S/m, σ_{fat} = 0.01 S/m, σ_{long} = 0.5 S/m, σ_{transv} = 0.1 S/m). The thickness of the skin was 1 mm. The thickness of the fat layer was 1-3-5 mm in three sets of simulations. The source was represented as a spatio-temporal function (analytical model from Rosenfalck, 1969) which describes generation, propagation, and extinction of the intra-cellular action potential at the end-plate, along the fiber, and at the tendons, respectively. The model is shown in Figure 1.

Figure 1 about here

Finite length fibers (140 mm long) symmetrical with respect to the innervation zone were simulated with density of one fiber per 4 mm^2. A single fiber action potential (SFAP) was used to simulate a MUAP, approximating the smoothing due to the spread of the innervation zone and tendon endings (8 mm) by a time convolution with a Gaussian window function. In this way, a fiber was considered as representative of a MU. Three libraries of 216 single differential (SD) SFAPs of fibers distributed uniformly within the muscle were simulated, each library corresponding to different values of the subcutaneous tissue thickness. From each of these libraries of SFAPs, different

libraries of MUAPs were built, considering different random distributions of MU sizes (number of fibers belonging to the MUs distributed as an exponential function with ratio of innervation numbers between the largest and the smallest units equal to 20 (Enoka and Fuglevand, 2001) and different CV Gaussian distributions, with mean varying across different simulations and standard deviation equal to 0.3 m/s. Each MUAP library was considered as corresponding to a simulated "subject".

MUs were recruited according to the exponential function proposed by Fuglevand and collaborators (1993), with range of recruitment thresholds equal to 75% of the maxima voluntary contraction (MVC). The discharge statistics were modelled assuming minimum and maximum discharge rates of 8 and 35 pulses per second (pps), linear relation between force and discharge rate (0.5 pps/%MVC for all MUs), and Gaussian distribution of the interpulse interval variability with coefficient of variation (COV) 0.2 considered (Farina et al., 2002)(Fuglevand et al., 1993). The MUs were recruited from lower to higher CV (Andreassen and Arendt-Nielsen, 1987).

A high contraction level of force (80% of MVC) was simulated in order to reduce the number of confounding factors. In this way all MUs were recruited and both load sharing between synergic muscles and possible recruitment/de-recruitment of MUs were not considered (Fuglevand et al., 1993).

The simulated signals were detected by an array of 8 rectangular electrodes, 4 mm long and 1 mm thick. The interelectrode distance was 5 mm. The electrode array was aligned to the direction of the muscle fibers and placed between the innervation zone and one of the tendons. The signals were detected in single differential (SD) configuration.

2.2 Simulation of fatigue

Two factors were simulated as manifestations of peripheral and central fatigue, respectively: 1. reduction of CV; 2. increase of MU synchronization (Holtermann et al., 2008).

Synchronization was simulated as proposed by Yao and collaborators (2000). Two parameters are used to set the level of synchronization: 1. the percentage of firings in each MU train synchronized with the firings of the other MUs (%F); 2. the number of firings synchronized together for each synchronization event, expressed as a percentage of the total number of MUs (%M) (Yao et al., 2000; Farina et al., 2002). For this application, it was assumed %F=%M and this percentage indicated the level of synchronization.

For the simulation of non stationary signals CV distribution changed linearly in time towards lower value of CV (the mean of the distribution changing from 4 m/s to 3 m/s in 30 s, with constant standard deviation) and synchronization increased linearly from 0% to 20%.

2.3 Assessment of estimation variance

The signals of twenty "subjects" were simulated in two conditions.

Simulation 1. Stationary signals were considered, i.e. with constant Gaussian CV distribution with mean 4 m/s and standard deviation 0.3 m/s and no synchronization (neither peripheral nor central fatigue was simulated).

Simulation 2. Non stationary signals were considered (CV decreasing from 4 m/s to 3 m/s in 30 s, synchronization increasing from 0% to 20% in 30 s).

Simulated signals (7 channels, SD, 30 s long) were divided into adjacent, non overlapping epochs (0.5 s long) for a total number of 60 epochs for each signal. Each index was applied on every epoch of the simulated signals. For methods working on single channels, the (spatial) average of the estimates from each channel was computed. The COV of the 60 estimates corresponding to the 60 epochs was evaluated for stationary signals, for each simulated signal and each index. In case of non stationary signals the slope (normalized with respect to the initial value) of the regression line for each estimated index was considered.

2.4 Assessment of sensitivity to peripheral and central fatigue

The sensitivity in detecting myoelectric manifestations of muscle fatigue was assessed applying the fatigue indexes to signals with different mean values of CV distribution and different levels of synchronization. Forty "subjects" were simulated.

Simulation 3. For each "subject", signals of duration 0.5 s with constant mean of CV distribution in the range 3-5 m/s, with 11 steps of 0.2 m/s, and synchronization level (%F = %M) in the range 0-20 %, with 11 steps of 2 %, were simulated obtaining a set of signals of dimension 11x11 (121 simulations) for each "subject". Both variables, mean CV and level of synchronization, were normalized by linearly mapping each to the range [0, 1], e.g. the signal simulated with CV = 3 m/s and synchronization level of 20% corresponded to the coordinates *(0, 1)* in the normalized map. For each "subject", fatigue indexes were computed as a function of two parameters: mean CV and synchronization level. Regression planes were then obtained for each index. The sensitivity of a fatigue index to a variation of each of the two parameters (CV and synchronization), was defined as the first and second component (respectively) of the unity vector normal to the regression plane.

2.5 Statistical analysis

A repeated measures one-way analysis of variance (ANOVA) was performed on the normalized slope and on the COV of each of the computed EMG indexes. Fat layer thickness (1, 3, and 5 mm) was the fixed factor for each ANOVA. Significance was set to $p < 0.05$.

2.6 Experimental signals

Surface EMG signals were recorded from the vastus lateralis muscle of a power trained and an endurance trained athlete during an isometric endurance test at 80% MVC. Signals were recorded using an adhesive array of 8 electrodes (5 mm interelectrode distance) aligned with the muscle fibers (data from Rainoldi et al., 2008 were used).

3. RESULTS

COV of the fatigue indexes (listed in Table 1) was estimated from Simulation 1 (60 epochs of stationary signals). Figure 2 shows the mean and standard deviation of the COV of the estimates of each index for a set of 20 simulated "subjects" with stationary EMG, in the case of 3 mm thickness of the fat layer. One-way ANOVA did not show statistically significant dependency of the COV of any of the EMG indexes on fat layer thickness.

Figure 2 about here

Figure 3 shows the mean and standard deviation of the 20 slopes (normalized with respect to the intercept) of the indexes estimated from 20 simulated "subjects", in the case of 3 mm thickness of the fat layer (results of Simulation 2). One-way ANOVA did not show statistically significant dependency of the normalized slope of any of the EMG indexes on fat layer thickness.

Figure 3 about here

Figure 4 shows the sensitivity of some of the fatigue indexes to a variation of CV or synchronization. The two components of the vectors normal to the regression plane of the estimates obtained from Simulation 3 were defined as explained in the Methods section for each of the 40 simulated "subjects". The vectors of each index were normalized with respect to the mean of the modulus across different subjects. ECV showed the minimum angle, close to 0°, indicating very high sensitivity to CV changes and very low sensitivity to synchronization, while FD showed the maximum angle, about 75°, indicating low sensitivity to CV changes and high sensitivity to synchronization). The indexes not shown (ARV, MDF, MNF_{CWT}, MNF_{CWD}, MNF_{AR}, FI_3, FI_4, FI_5, %DET, S) showed behaviour similar to that of MNF, showing lower selectivity to central and peripheral fatigue. The vector *(ECV, FD)*, referred in the following as fatigue vector, was then chosen to provide a quantitative indication of myoelectric manifestation of fatigue, with the first

and second component giving predominantly indication of peripheral and central fatigue, respectively.

Figure 4 about here

Figure 5 shows the comparison between MNF and FD with different values of fat layer. Each plot shows the values of mean and standard deviation (across 40 simulated "subjects") of MNF and FD computed from epochs of stationary signals with mean of CV distribution in the range 3-5 m/s and levels of synchronization 0% - 10% - 20% (simulation 3). The fat layer thickness was set to 1 mm and 5 mm (with 3 mm thickness providing intermediate results).

Figure 5 about here

Figure 5 shows that MNF decreases when fat layer thickness increases (as documented in the literature). Furthermore, MNF is affected by both CV and MU synchronization. On the contrary, FD is weakly affected by either CV (refer also to Figure 4) or fat layer thickness. FD is indeed mainly affected by the level of MU synchronization. This allows distinguishing between synchronization levels of 0% and 20%, in all the simulated conditions, while such information cannot be extracted from the values of MNF.

Figure 6 shows the ECV, FD and MNF obtained from the signals recorded on vastus lateralis muscle of A) a power trained subject and B) an endurance trained subject during an isometric contraction at 80% MVC. For the power trained subject, the rate of change of ECV is high, but FD does not have a clear trend, indicating that the level of synchronism does not change. For the endurance trained subject, the rate of change of ECV is lower than in the case of the power trained subject, but FD decreases during the task, indicating that the level of synchronism increases as an adaptation to muscle fatigue.

Figure 6 about here

4. DISCUSSION

Fatigue indexes provide a quantitative measure of the variation of the properties of the surface EMG signal during a fatiguing contraction. Such properties are: 1) amplitude, 2) spectral features, 3) muscle fiber CV, 4) non linear features of the signal. Different indexes of each of these properties show different performances, depending on the contraction type (more or less fatiguing, isometric or dynamic). Different fatigue indexes have been applied in this study to the same set of surface EMG signals simulated by a structure based model, with the purpose of comparing them and of identifying indexes giving a selective estimate of either peripheral or central manifestations of fatigue.

4.1 Limitations of the simulation model

Interpretation of the results cannot disregard the limitations of the model of simulation, which is based on a number of assumptions and approximations. Simulating the myoelectric manifestations of fatigue is indeed very complicated and is still an open research issue. Our simulated signals are based on assumptions which could be questionable. Simple hypotheses were made in order to focus only on some of the main aspects of the problem, as including all the physiological manifestations of fatigue in a model is not possible at the moment. Only two manifestations of muscle fatigue were simulated: CV variation and MU synchronization. Other manifestations of muscle fatigue are the recruitment of different MUs and the interplay of firing rate and recruitment (these manifestations are reduced in the case of the high simulated contraction level, but cannot be excluded in experiments). If more muscles are active on the same joint, variations of load sharing can take place. The assumption that the force and the MU pool are strictly constant during the contraction is not reasonable in real experiments. In addition, muscle fatigue could induce changes in the shape of the intracellular action potential (observed in vitro experiments on animals and modelled in many publications (Arabadzhiev et al., 1991), even though there is no data from in vivo experiments in humans and it is not possible to choose properly the supposed enlargement of the negative after-

potential). CV distribution was assumed to be Gaussian and only the mean of the distribution was varied in different simulations of fatigue, even if muscle fibers of different types present different variations of CV during a fatiguing contraction. Different methods have been proposed in the literature to model the physiological mechanisms involved in MU synchronization. Since no consensus was found about the best method, we adopted the algorithm proposed by Yao and collaborators (2000). Furthermore, we assumed no synchronized motor unit at the beginning of the contraction. Nevertheless, the results are based on percentage changes of indexes with respect to the initial value. As far as the variation of the indexes with the level of synchronism is approximately linear, the results can be considered valid also to the case in which the initial level of synchronism in different from 0%.

4.2 Fatigue indexes applied in the literature

All investigated indexes, with the exception of S, have been already applied in the literature to estimate fatigue due to both peripheral and central phenomena. The spectral indexes proposed by Dimitrov and collaborators (indicated with FI_k) were applied to both M-waves (Dimitrova et al., 2005) and interference signals (Dimitrov et al., 2006), as well as to simulated and real signals. A high sensitivity to myoelectric manifestations of fatigue was shown. Spectral variables estimation with periodogram and AR based methods were investigated in (Farina and Merletti, 2000). AR methods performed slightly better in case of short epochs or non stationary conditions. It was shown in (Farina et al., 2002) that %DET is sensitive to both CV changes and synchronization of MUs, giving higher relative variations than spectral variables. However, the computation of %DET requires careful tuning of parameters and a time consuming set of attempts by trial and error. Different TFR methods were compared in (Karlsson et al., 1999) (static contractions) and in (Karlsson et al., 2000) (dynamic contractions) indicating that the wavelet transform has the best accuracy and precision in estimating changes of surface EMG signals. However, our findings show that this approach, as well as approaches based on spectral changes, does not differentiate between

changes of CV and of degree of synchronization. It was pointed out that FD of surface EMG signal is highly correlated to the force level (Gitter and Czerniecki, 1995). Some EMG spectral parameters related to fractals were studied in the case of voluntary isometric contractions of biceps brachii muscle (Ravier et al., 2005). The proposed fractal indicator was sensitive to different force levels, but insensitive to fatigue. The behaviour of FD index was assessed in a recent study (Troiano et al. 2008) during isometric contractions of upper trapezius muscle. The results indicate that FD of signals recorded during short, non fatiguing contractions is not affected by different force levels. On the other hand, FD estimated during an endurance contraction at 50% MVC is sensitive to fatigue and is predictive of endurance time.

4.3 Reliability of fatigue indexes

A preliminary analysis of reliability of the fatigue indexes based on simulated signals was performed in this study. The COV was estimated on 20 stationary signals. MNF had a higher level of reliability, compared to amplitude estimations. The spectral index FI_k showed a high variation between epochs, indicating low reliability. Non linear properties measured by %DET, extracted from RQA analysis, also had a high COV. This could be related to the choice of the parameters, which were fixed after searching for the best values on a small subset of simulated signals. On the contrary, S had a very low COV and FD showed a COV of the same order of MNF. ECV resulted as the variable which can be estimated with the lowest error when computed with a multi-channel approach.

Different distributions of MUs within the muscle and different fat layer thicknesses were simulated assuming fibers parallel to the skin and to the electrode array. These configurations could be interpreted as corresponding to different subjects. For the same fat layer thickness, all parameters in the simulations (CV distribution, anatomy) remained constant except when MU locations change. This situation resembles also the experimental case of placing the electrode array in a different position over the same muscle of the same “subject”, as the MUs contributing to the recorded signal

are different, but the anatomy remains the same. This means studying the problem of constancy (that is the assessment of estimate variation in different time or position) (Viitasalo and Komi, 1957).

ECV (when estimated by a multi-channel algorithm) was observed to be the least sensitive but the most robust index, with respect to both MU distribution and fat thickness variation. All other indexes were affected by such anatomical factors, except for FD, which is weakly affected by fat layer thickness.

4.4 Global estimation of fatigue

The methods were also applied to non stationary signals, characterised by CV decrease and MU synchronization increase in time. The variation of the normalized slope of the indexes for different MU distributions was assessed, expressing the capability of giving a global estimation of fatigue. The spectral indexes FI_k and %DET were sensitive to a variation of simulated CV and level of synchronism, with the indexes FI_k giving the highest normalized slope, but they had the highest variance because were the most sensitive to MU distribution, limiting the possibility of comparing EMG fatigue in different subjects. Amplitude and frequency indexes had a comparable sensitivity both to the simulated EMG fatigue condition and to MU distribution. S showed a very low sensitivity to myoelectric manifestations of fatigue, possibly due to the opposite effects of CV decrease and synchronization increase on S (see Appendix). Also FD showed a low variation. This is likely due to the fact that FD is sensitive primarily to central fatigue and not to peripheral fatigue. CV provided a high sensitivity to the simulated manifestation of fatigue, being also robust to MU distribution in the muscle. It is to note that most of the factors that are known to introduce biases in ECV and to decrease its reliability (motion artefacts, local inhomogeneities, array misalignments, etc see (Farina and Merletti, 2004) for a complete list) were not simulated in this work.

4.5 Selective estimation of fatigue

The capability of the indexes to provide selective information on either peripheral or central myoelectric manifestation of fatigue was assessed. It was observed that ECV is uncorrelated to the level of simulated synchronization, and it is the most promising method for the estimation of peripheral fatigue. On the contrary, FD is the index least affected by CV changes and by fat layer thickness, and mostly related to the level of synchronism, and therefore being the most promising index of this manifestation of central fatigue. All other fatigue indexes gave a global estimation of EMG fatigue, being sensitive to both variations of CV and MU synchronization.

It is suggested that myoelectric manifestations of fatigue can be better described if two distinct measures of peripheral and central fatigue are used rather than a single index. The representative example of application to experimental signals from athletes of different disciplines (a power trained and an endurance trained athlete to create a large contrast in fiber type composition, see Figure 6) shows that the fatigue vector can provide useful information to distinguish between different recruitment strategies and peripheral adaptations to fatigue.

As shown in Figure 4, the vector *(ECV, FD)* resulted promising from this simulation study. Nevertheless, further studies are suggested to support this choice of the two components of the fatigue vector. The main problem is the assessment of repeatability of the two components, which is in general of paramount relevance for the clinical daily use of surface EMG. To reach this goal it is necessary to define the minimum change of the observed variables that may reflect physiological variations and not random fluctuations. This assessment is a precondition to demonstrate the potential clinical usefulness of the new surface EMG technique proposed. Several works on repeatability of surface EMG variables on many different muscles, such as elbow flexors, quadriceps, back, and respiratory muscles, can be found in the literature of the last decade (Bilodeau et al., 1994; Linssen et al., 1993; Merletti et al., 1998; Ng and Richardson, 1996; Rainoldi et al., 1999; Rainoldi et al., 2001; Dedering et al., 2000; Kollmitzer et al., 1999). They similarly concluded that ECV is the variable which can be estimated with the lowest error and that MNF is the variable which can be estimated with the highest level of repeatability within subjects. The

repeatability of FD is still to be assessed. A further open issue is the behaviour of these indexes in dynamic contractions and their sensitivity to muscle shifts under the electrode array.

5. CONCLUSIONS

Although the concept of fatigue vector extracted from surface EMG is not new (Merletti et al., 1991), the description based on the relative role of both peripheral and central fatigue was not previously suggested. A two dimensional vector can give a more detailed description of the myoelectric manifestation of fatigue than a scalar index. The vector *(ECV, FD)* is suggested in this study, as it is constituted by two independent indexes of predominantly peripheral (decrease of CV) and central fatigue (increase of synchronization), respectively. The description of EMG fatigue by a bi-dimensional vector opens new perspectives in the assessment of muscle properties, with potential application in both clinical and sport sciences. As a future perspective, myoelectric manifestations of muscle fatigue other than the decrease of CV and the increase of MU synchronization could be investigated and other indexes, providing selective information to specific manifestations of fatigue, could be suggested.

APPENDIX

Simulated signals were divided into 0.5 s long epochs. From each epoch, the fatigue indexes described in the following were estimated: mean frequency – MNF; median frequency – MDF; root mean square – RMS; average rectified value – ARV; estimated conduction velocity – ECV, and recently proposed methods based on recurrence quantification analysis – RQA; spectral indexes proposed by Arabadzhiev and collaborators (Arabadzhiev et al., 1991); time-frequency

representations – TFR; continuous wavelet transform – CWT; entropy - S, and fractal dimension – FD.

Classical methods

Variables traditionally used for information extraction from surface EMG signals are those providing indication on global amplitude, spectral content, and conduction velocity. As surface EMG is non stationary, signals are divided into epochs of short duration where the WSS can be assumed.

EMG average amplitude increases as the muscle undergoes fatigue, reflecting the decrement in CV, the possible recruitment of new MUs, the increment of firing rate, the increasing synchronization of MUs. The amplitude measurements that we considered are the following

$$ARV = \frac{1}{T}\int_0^T |EMG(t)|dt \qquad RMS = \sqrt{\frac{1}{T}\int_0^T EMG(t)^2 dt} \tag{1}$$

In order to reduce the estimation variance, amplitude was estimated after whitening (i.e., decorrelating the samples of the EMG signal; the method (Clancy and Farry, 2000) is based on the cascade of a non adaptive whitening filter, an adaptive Wiener filter, and an adaptive gain correction).

During fatiguing contractions, the power spectral density PSD, evaluated for each epoch of the EMG signal (periodogram), moves progressively toward lower frequencies. This phenomenon is indicated as spectral compression, even though the PSD is not simply scaled during fatigue. For this reason, different spectral variables provide different information. Two spectral variables were considered in this study, MNF and MDF, defined below

$$MNF = \frac{\int_0^{f_s/2} f\, PSD(f)df}{\int_0^{f_s/2} PSD(f)df} \qquad \int_0^{MDF} PSD(f)df = \int_{MDF}^{f_s/2} PSD(f)df \tag{2}$$

where f_s is the sampling frequency.

An alternative method with respect to the Fast Fourier transform (FFT) for the estimation of PSD is based on a parametric approach (autoregressive analysis – AR; autoregressive moving average – ARMA, see Merletti and Parker, 2004). The signal is considered as the output of a linear time invariant (LTI) filter with white noise as input. AR analysis was considered in this study. The general transfer function of an AR model of order q

$$H(e^{j\omega}) = \sum_{k=0}^{q} a_k e^{jk\omega} \quad (3)$$

is determined by estimating the parameters a_k from the EMG signal. PSD is obtained as the squared magnitude of H and spectral indexes can be estimated from (2).

Muscle fiber CV is a physiological parameter related to fiber type and diameter, ion concentration, pH, muscle temperature and MU firing rate (Andreassen and Arendt-Nielsen, 1987; Arendt-Nielsen and Zwarts, 1989; Brody et al., 1991). Different methods for CV estimation have been proposed in the literature (Farina and Merletti, 2004). The multi-channel approach proposed by Farina and collaborators (Farina et al., 2001), was adopted in this paper using double differential (DD) signals.

Advanced methods

1. RQA

Nonlinear tools have been recently introduced for fatigue assessment from single channel surface EMG signals. The neuromuscular system is considered as a dissipative dynamical system governed by a set of D non linear, first order, ordinary differential equations, where D is the number of state variables. The system dynamics can be studied from a single time series (Takens et al., 1981), i.e. a single output of the system (which is the sampled EMG signal for the problem at hand). The signal is embedded into a D-dimensional space. Each state of the dynamical system is represented by a D-dimensional vector v(n) obtained lagging the data by an integer number λ. A binary recurrence map (with values ON / OFF) is obtained by assigning value ON to the entry (i,j) if the euclidean distance between the i^{th} and the j^{th} vector is larger than a threshold TH (expressed as a percentage of the maximum distance), and value OFF otherwise. Different indexes can be extracted from the

recurrence map (Webber and Zbilut, 1994). An index which was shown to be promising for the detection of muscle fatigue is the percentage of determinism - %DET (Farina et al., 2002), defined as the percentage of points that form upward lines parallel to the diagonal of the recurrence map (with length higher than a cutoff value L) with respect to the total number of entries with value ON.

2. New spectral indexes

In recent studies (Dimitrov et al., 2006; Dimitrova et al., 2000), Dimitrov and collaborators proposed new fatigue indexes, defined as the ratio between the signal spectral moment of order (-1) and those of order 2-5

$$FI_k = \frac{\int_{f_1}^{f_2} f^{-1} PSD(f) df}{\int_{f_1}^{f_2} f^{k} PSD(f) df} \qquad k = 2,3,4,5 \tag{4}$$

where f_1 and f_2 define the bandwidth of the EMG signal (f_1=20 Hz and f_2=500 Hz in this study).

3. TFR and CWT

Specific tools have been developed to study non-stationary signals such as (TFR). The distribution of the energy of the signal is represented in the time-frequency domain. A spectral variable (e.g., MNF, MDF) can be estimated by averaging in the frequency space, obtaining the instantaneous value of the variable as a function of time. An example of linear TFR is the short time Fourier transform (STFT)

$$STFT_{x,w}(t, f) = \int_{-\infty}^{+\infty} x(\tau)\, w^*(\tau - t)\, e^{-j2\pi ft}\, d\tau \tag{5}$$

where x is the signal to be transformed, w is the window (usually Gaussian) selecting the time interval of interest (Gabor, 1946). The square magnitude of the STFT is the spectrogram. Another linear TFR is the wavelet transform

$$CWT_{x,\psi}(a,b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{+\infty} x(t) \psi^* \left(\frac{t-b}{a} \right) dt \tag{6}$$

where ψ is the mother wavelet, a is the scale factor (related to frequency by the relation $f = \frac{f_0}{a}$, where f_0 is the central frequency of the spectrum of the mother wavelet), and b is the translation parameter (time shifting). The first derivative of a Gaussian function was chosen as mother wavelet in this study (Lo Conte et al., 1994). The square magnitude of the CWT is the scalogram. The essential difference between STFT and CWT is the different time-frequency resolution, which is uniform in the time-frequency domain for STFT, whereas, in the case of CWT, time resolution improves at high frequencies and frequency resolution increases at low frequencies (Rioul and Vetterli, 1991).

Quadratic TFR can also be used to estimate time-frequency energy distribution, since energy is a quadratic property of the signal. Wigner-Ville distribution is defined as

$$W_{x,}(t, f) = \int_{-\infty}^{+\infty} x\left(t + \frac{\tau}{2}\right) x^*\left(t - \frac{\tau}{2}\right) e^{-j2\pi f\tau}\, d\tau \qquad (7)$$

As Wigner-Ville operator is quadratic, it is affected by cross-terms. The effect of cross-terms can be reduced by trying to attenuate their contribution using a kernel (Cohen class distributions, see Cohen, 1989). A possible choice is a Gaussian kernel, which is used in the Choi-Williams distribution (CWD)

$$CWD_{x,}(t, f) = \int_{-\infty}^{+\infty}\left[\frac{1}{\sqrt{4\pi\tau^2/\sigma}} \exp\left(-\frac{(\mu - t)^2}{4\tau^2/\sigma}\right) x\left(\mu + \frac{\tau}{2}\right) x^*\left(\mu - \frac{\tau}{2}\right) d\mu\right] e^{-j2\pi f\tau}\, d\tau \qquad (8)$$

where σ is a scaling factor which trades off auto-term resolution and cross-term suppression.

4. Entropy

In the field of information theory, entropy is introduced as a measure of complexity (it is a non linear property). The definition of information entropy is the following

$$S = -\sum_{i=1}^{N} p_i \log_2 p_i \qquad (9)$$

where p_i is the probability of the ith outcome of the signal considered as a random variable taking N possible values (sampled amplitude of the signal within the epoch). Following the idea of Farina and collaborators (2006), modified entropy was used, for which the probability density was proportional to the energy of the signal. For the epoch and sampling frequency considered, with N=1024 samples, the maximum and minimum values of entropy are $\log_2 N=10$ and 0, respectively. If all the outcomes are equally likely, the information entropy is maximum. This suggests that S should decrease when synchronism increases and should increase when muscle fiber CV decreases. Due to these opposite factors the behaviour of S with fatigue is not trivial.

5. Fractal dimension

The measure of a one dimensional – 1D - object (a curve) is given by its length, the measure of a two dimensional – 2D - object (a surface) is quantified by its surface area. It is possible to define recursively self-similar curves which have infinite length, but vanishing area (e.g., von Kock's curve). Fractal dimension (FD) is the dimension of the space in which the considered curve has a finite, non vanishing measure. It can be defined as the exponent FD in the expression

$$n(\varepsilon) = \varepsilon^{-FD} \qquad (10)$$

where $n(\varepsilon)$ is the minimum number of open sets of diameter ε needed to cover the curve. It is possible to check that this definition is consistent with that of 1D and 2D (i.e., the fractal dimension of a line is 1 and that of a simple surface is 2).

A signal can be considered as a curve in the time-amplitude space, so that FD of a signal can be computed. In general the FD of a signal takes values between 1 (smooth signals) and 2 (stochastic or deterministic signals filling the whole space). As an example, Brownian motion has FD 1.5. Hence, FD gives a quantitative indication of the chaotic behaviour of the signal. It is related to the high frequency content of the signal, which is inversely related to the "smoothness" of a signal.

The box counting method was applied to estimate FD (Gitter and Czerniecki, 1995). A set of square boxes are used to cover the signal. When decreasing the side of the boxes in a dichotomic process,

the number of boxes required to cover the signal increases exponentially. The range of box size is restricted in order to avoid saturation for high and low value of size (Gitter and Czerniecki, 1995). Plotting the logarithm of the number of boxes required to cover the signal versus the logarithm of the inverse of the box area, an approximately linear relation is obtained. The slope of the interpolation line (estimated in the least mean squared sense) is the fractal dimension. As FD of EMG signals cannot be less than 1, in this paper FD was defined as the excess of the fractal dimension with respect to 1, obtaining a number between 0 and 1. The following expression holds:

$$FD = \frac{\log N}{\log \frac{1}{L}} - 1 \qquad (11)$$

where N is the number of boxes required to cover the signal and L is the box side, with the ratio indicating the slope of the interpolation line.

List of acronyms

ANOVA: Analysis of Variance; AR: Auto Regressive; ARV: Average Rectified Value; COV: Coefficient of Variation; CV: Conduction Velocity; CWD: Choy Williams Distribution; CWT: Continuous Wavelet Transform; %DET: Percentage of Determinism; DD: Double Differential; EMG: Electromyography; FD: Fractal Dimension; FFT: Fast Fourier Transform; FI_k: Fatigue Index of order k; MDF: Median Frequency of the power spectrum estimated by FFT; MNF: Mean Frequency of the power spectrum estimated by FFT; MNF_{AR}: Mean Frequency of the power spectrum estimated by AR analysis; MNF_{CWD}: Mean Frequency of the power spectrum estimated by CWD; MNF_{CWT}: Mean Frequency of the power spectrum estimated by CWT; MU: Motor Unit; MUAP: Motor Unit Action Potential; MVC: Maximal Voluntary Contraction; PDF: Power Density Function; pps: pulses per second; PSD: Power Spectral Distribution; RMS: RQA: Recurrence Quantification Analysis; S: Entropy; SD: Single Differential; SFAP: Single Fiber Action Potential; STFT: Short Time Fourier Transform; TFR: Time Frequency Representation; WSS: Wide Sense Stationary.

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TABLE 1: list of the fatigue indexes

Index	Acronym	Comments/Parameters
Average Rectified Value	ARV	Whitening
Root Mean Square Value	RMS	Whitening
Mean Frequency (from periodogram)	MNF	
Median Frequency (from periodogram)	MDF	
Mean Frequency (from CWD)	MNF_{CWD}	σ□= 0.5
Mean Frequency (from CWT)	MNF_{CWT}	Mother wavelet: first derivative of a Gaussian function
Mean Frequency (from AR analysis)	MNF_{AR}	q=5
Determinism	%DET	λ = 1 sample, D = 7, L = 10 samples, TH = 20% - signal undersampled by a factor 2
Other spectral indexes	FI_k	k=2, 3, 4, 5
Entropy	S	
Fractal Dimension	FD	Box size in pixels: $2^3 < S < 2^{11}$
Conduction velocity	ECV	6 DD channels, maximum likelihood approach

5

FIGURE CAPTIONS

Figure 1. Non-homogeneous (layered), anisotropic, planar volume conductor model constituted by muscle (anisotropic), fat (isotropic), skin (isotropic) layers. The volume conductor is infinite in x and z directions and semi-infinite in y direction. Fat layer thickness varies in Simulation 1, 2, and 3. Single fibers represent individual MUs. An array of 8 electrodes was placed along the direction of the MUs. The MUs are symmetric with respect to the innervation zone and are uniformly distributed inside a rectangular portion of the muscle layer, with density equal to one MU per 4 mm^2 (with a total number of 216 MUs). Fibers are parallel to the skin surface and to the electrode array. Conductivities are: σ_{skin} = 1 S/m, σ_{fat} = 0.01 S/m, σ_{long} = 0.5 S/m, σ_{transv} = 0.1 S/m.

Figure 2. Coefficient of variation (COV) of the estimates of the indexes listed in Table 1 and obtained from 60 epochs (0.5 s long) of stationary interference signals (Simulation 1). Mean and standard deviation of the COV on a set of 20 simulated "subjects" are shown (3 mm thickness of the fat layer). Individual estimates of indexes are obtained as the spatial average of the seven estimates from the SD channels of the electrode array. ECV is obtained using the multi-channel technique on six DD channels.

Figure 3. Mean and standard deviation of the normalized rate of change of the indexes obtained from 20 simulated "subjects" with the methods listed in Table 1 (Simulation 2). For each "subject". The normalized slope was computed from the regression line evaluated from 60 epochs (0.5 s each) of a non stationary interference signal (the mean of CV distribution changes linearly in time from 4 m/s to 3 m/s in 30 s. At the same time, synchronism increases linearly from 0% to 20%). The slope is either positive or negative, depending on the index chosen. The fat layer is 3 mm thick.

Figure 4. Results of Simulation 3. Sensitivity of ECV, RMS, MNF, FI_2 and FD to peripheral and central fatigue (i.e., to a variation of CV or synchronization, respectively). The sensitivity to these manifestations of fatigue is defined as the two components of the vector of the best fit plane of the estimates as a function of simulated CV and synchronism. The mean and standard deviation of the two components of such a vector obtained from 40 simulated "subjects" are shown (after normalisation of the unity vectors of each index with respect to the mean modulus across different subjects).

Figure 5. Effect of the fat layer thickness (1 mm in A,C, 5 mm in B,D) on MNF and (A,B) and on FD in (C,D). The two indexes MNF and FD are computed on epochs (0.5 s long) of stationary signals (mean of CV distribution in the range 3-5 m/s; levels of MU synchronization 0% - 10% - 20%). Mean and standard deviation (across 40 simulated subjects) are shown.

Figure 6. ECV, FD and MNF from surface EMG signals detected on vastus lateralis muscle during an isometric contraction at 80% MCV from a power trained subject A) and an endurance trained subject B).

Figure 1.

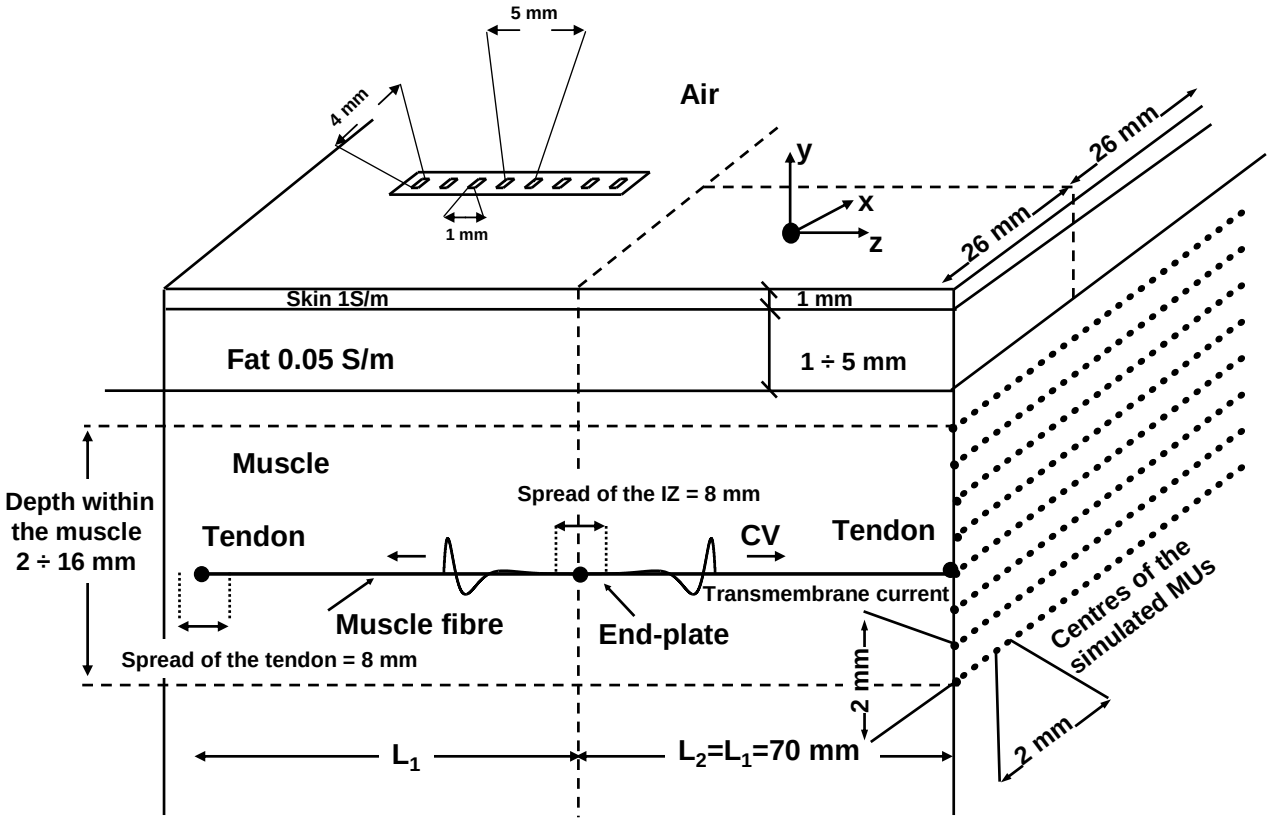

5 mm
4 mm
1 mm
Air
y
x
z
26 mm
26 mm
Skin 1S/m
1 mm
Fat 0.05 S/m
1 ÷ 5 mm
Muscle
Depth within the muscle 2 ÷ 16 mm
Spread of the IZ = 8 mm
Tendon
CV
Tendon
Transmembrane current
Muscle fibre
End-plate
Spread of the tendon = 8 mm
Centres of the simulated MUs
2 mm
2 mm
L1
L2=L1=70 mm

Figure 2.

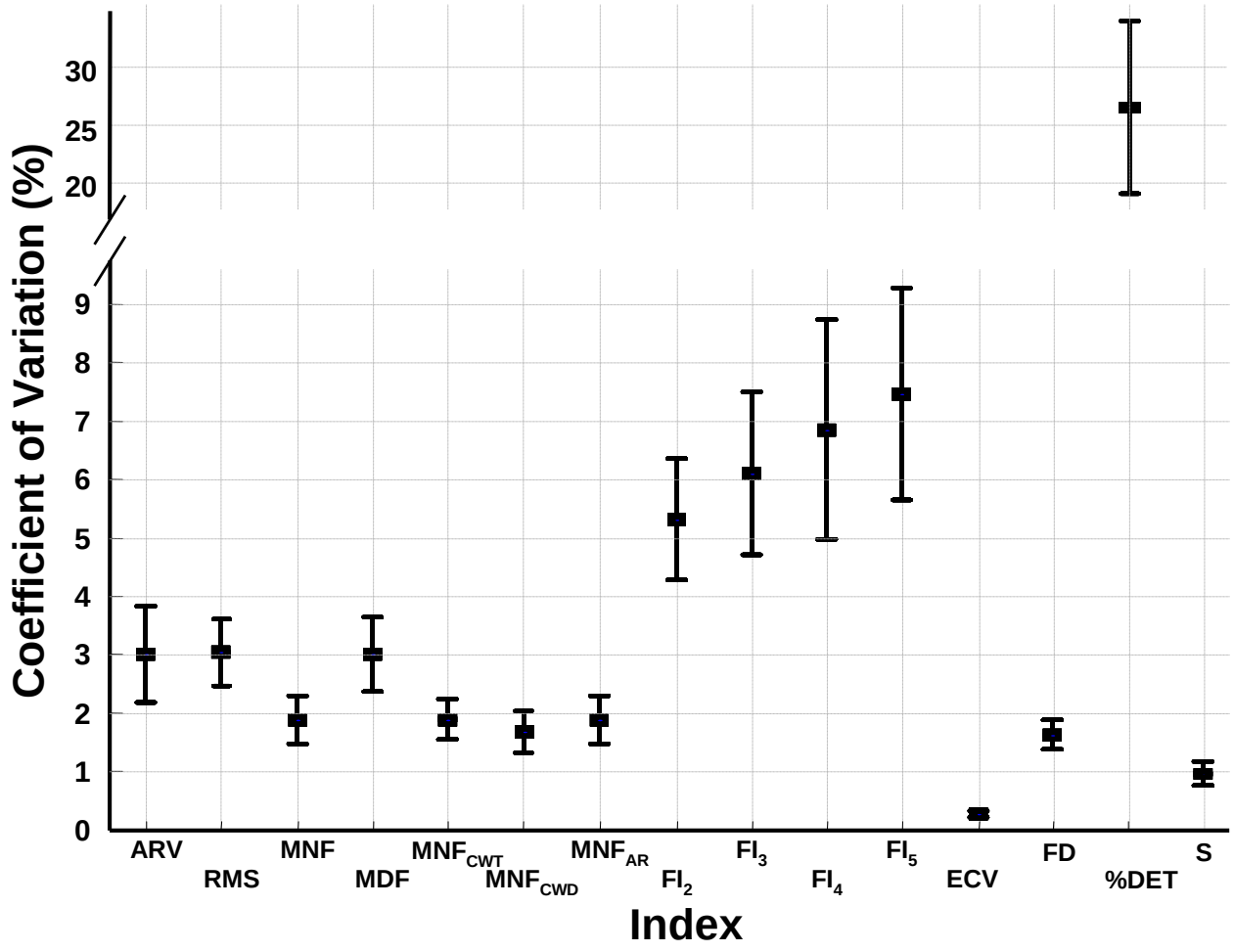

Coefficient of Variation (%)
30
25
20
9
8
7
6
5
4
3
2
1
0
ARV
RMS
MNF
MDF
MNF$_{CWT}$
MNF$_{CWD}$
MNF$_{AR}$
FI$_2$
FI$_3$
FI$_4$
FI$_5$
ECV
FD
%DET
S
Index

Figure 3.

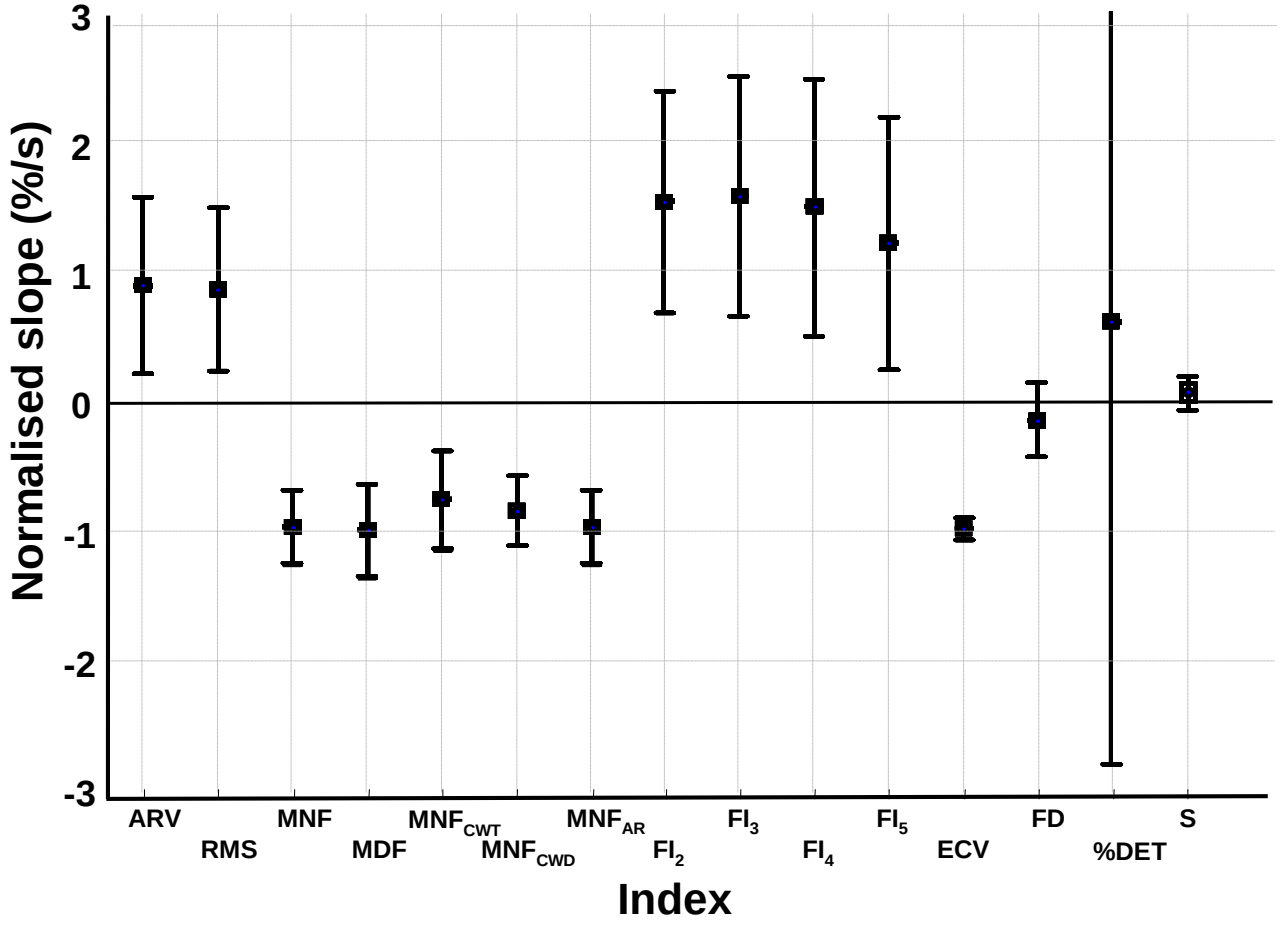

Normalised slope (%/s)
3
2
1
0
-1
-2
-3
ARV
RMS
MNF
MDF
MNF$_{CWT}$
MNF$_{CWD}$
MNF$_{AR}$
FI$_2$
FI$_3$
FI$_4$
FI$_5$
ECV
FD
%DET
S
Index

Figure 4.

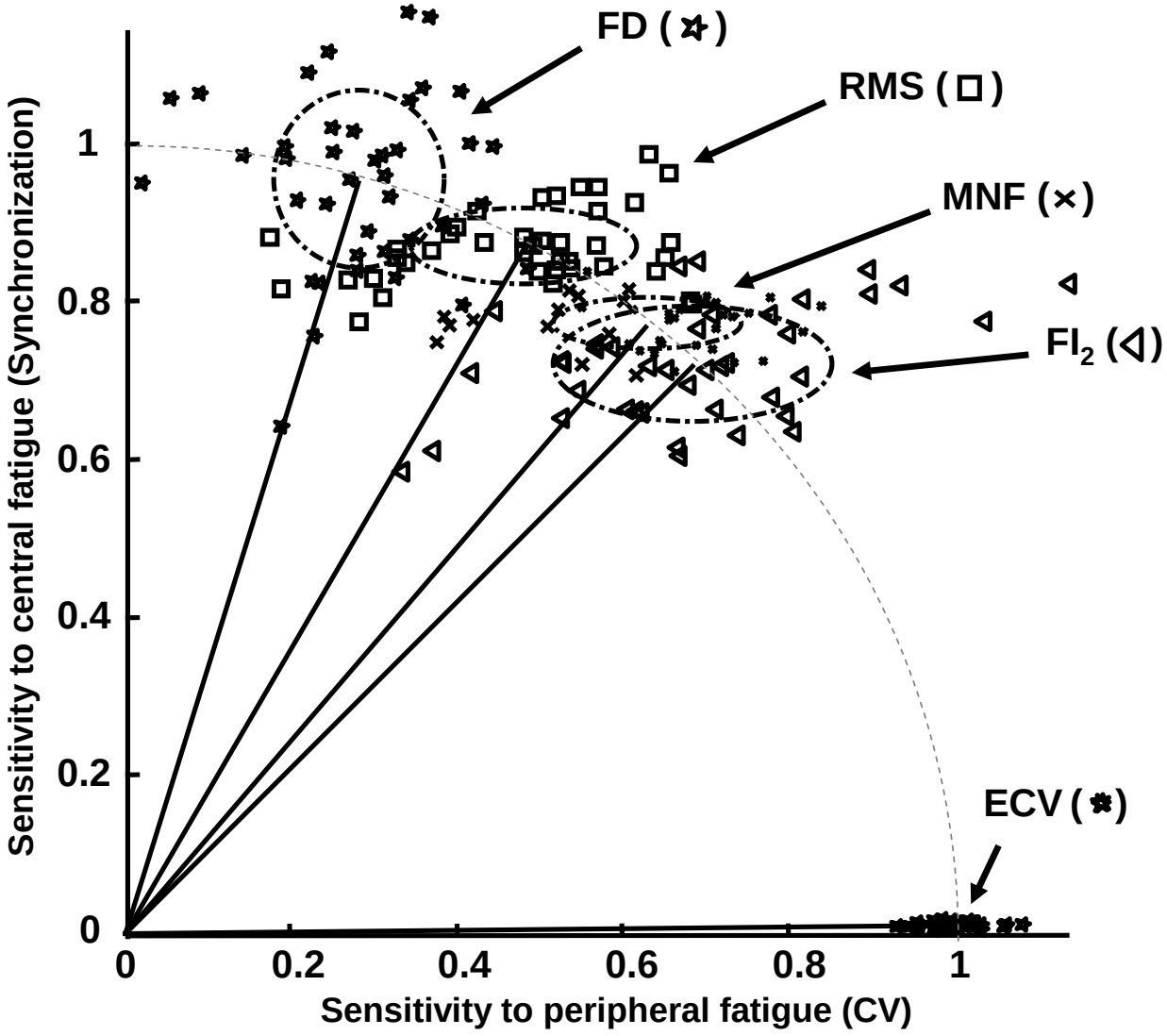

FD ( )
RMS ( )
MNF (×)
FI2 ( )
ECV ( )
Sensitivity to central fatigue (Synchronization)
Sensitivity to peripheral fatigue (CV)
0
0.2
0.4
0.6
0.8
1

Figure 5.

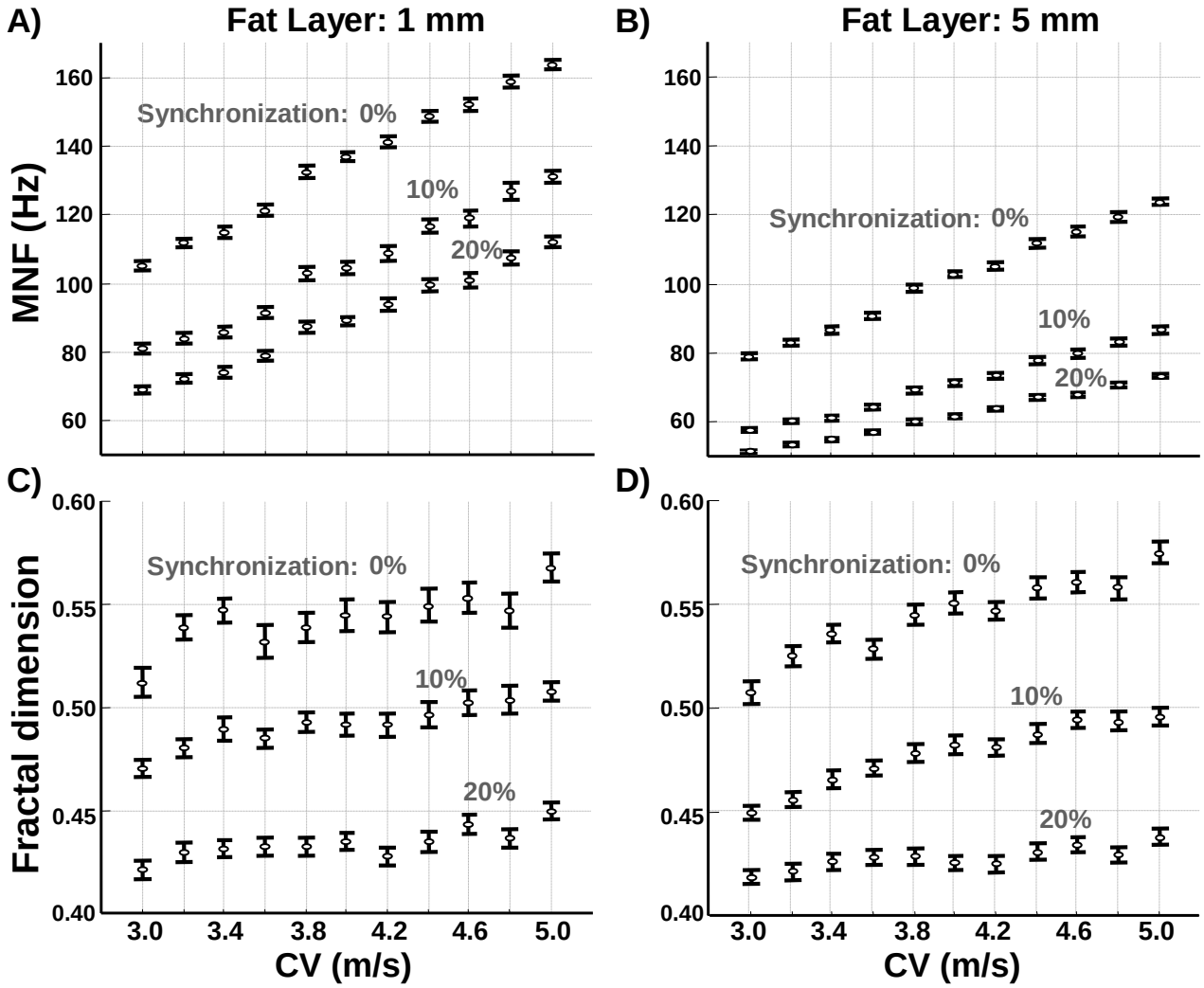
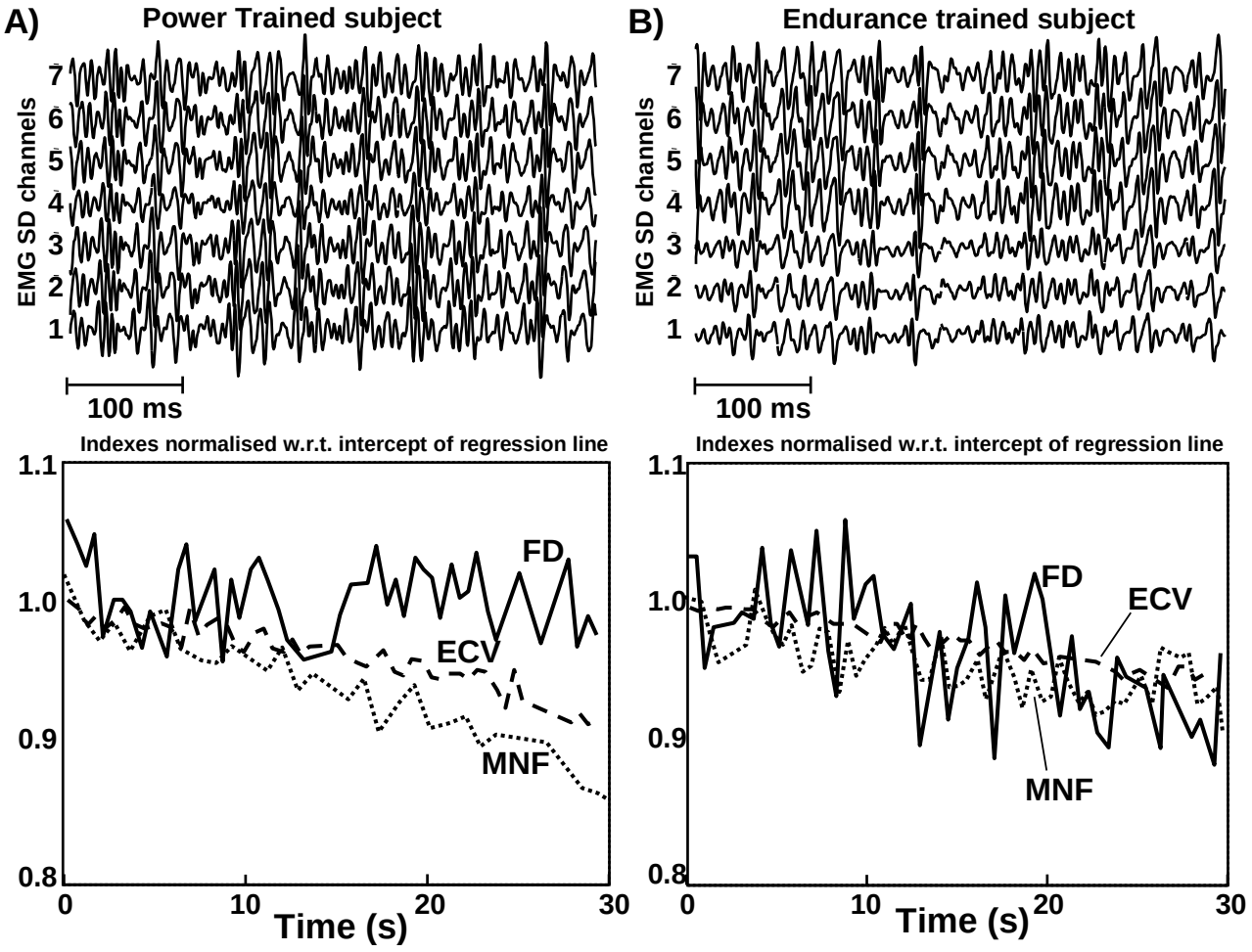

A)
Fat Layer: 1 mm
B)
Fat Layer: 5 mm
MNF (Hz)
Synchronization: 0%
10%
20%
C)
D)
Fractal dimension
CV (m/s)
160
140
120
100
80
60
0.60
0.55
0.50
0.45
0.40
3.0
3.4
3.8
4.2
4.6
5.0

Figure 6.


A)
Power Trained subject
EMG SD channels
7
6
5
4
3
2
1
100 ms
Indexes normalised w.r.t. intercept of regression line
1.1
1.0
0.9
0.8
FD
ECV
MNF
0
10
20
30
Time (s)
B)
Endurance trained subject
EMG SD channels
7
6
5
4
3
2
1
100 ms
Indexes normalised w.r.t. intercept of regression line
1.1
1.0
0.9
0.8
FD
ECV
MNF
0
10
20
30
Time (s)